Science of the Total Environment 660 (2019) 236–244

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Impacts of climate change and human activities on grassland vegetation variation in the Chinese Loess Plateau

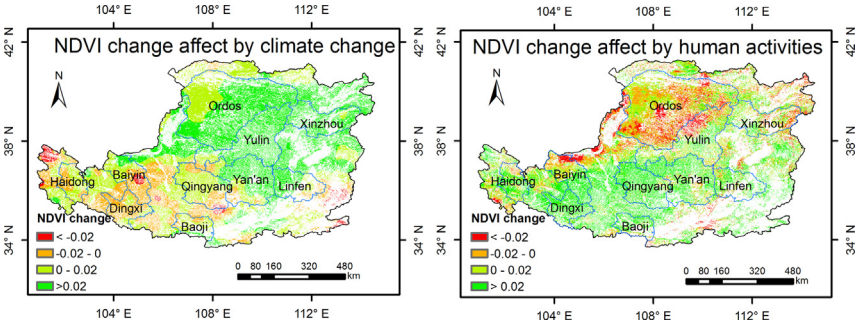
Kai Zheng, Jian-Zhou Wei, Jiu-Ying Pei, Hua Cheng, Xu-Long Zhang, Fu-Qiang Huang, Feng-Min Li *, Jian-Sheng Ye *

State Key Laboratory of Grassland Agro-ecosystems, Institute of Arid Agroecology, School of Life Sciences, Lanzhou University, No. 222, South Tianshui Road, Lanzhou 730000, China

HIGHLIGHTS

- Novel method was developed to distinguish climate change and human activities.
- Human activities contributed 42.35% to the vegetation change.
- Climate change contributed 57.65% to the vegetation change.
- The "Grain for Green Project" was the main human influence on vegetation.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 19 September 2018
Received in revised form 3 January 2019
Accepted 3 January 2019
Available online 4 January 2019

Editor: Ralf Ludwig

Keywords:
Vegetation change
Climate change
Human activities
Grain for Green Project
Loess Plateau

ABSTRACT

China initiated the "Grain for Green Project" in 1999 to mitigate soil erosion. The vegetation cover of the Chinese Loess Plateau, one of the most erosive regions in the world, has been greatly increased. However, studies on quantitatively investigating the climate change and human activities on vegetation coverage change were rare. In this study, spatio-temporal changes in vegetation coverage were investigated using MODIS normalized difference vegetation index (NDVI) data over 2000–2016. And a new method was introduced using Net Primary Productivity (NPP) model and relationship between NPP and NDVI to quantitatively and spatially distinguish the NDVI affected by climate change and human activities. Results showed that mean NDVI value over 2009–2016 were 14.46% greater than that over 2000–2007. In order to quantify the contribution of climate change and human activities to vegetation change, an NPP model suitable for the grassland of the Chinese Loess Plateau was identified using biomass observations from field survey and literature. The NDVI affected by climate change ($NDVI_{climate}$) was estimated by the NPP model and the relationship between NPP and NDVI. And the NDVI affected by human activities ($NDVI_{human}$) was calculated by actual NDVI minus $NDVI_{climate}$. Comparison of the two stages showed that human activities and climate change contributed 42.35% and 57.65% respectively to the ΔNDVI on grassland in the Loess Plateau. After analysis of numerous $NDVI_{human}$ related factors, the slopes restored by the "Grain for Green Project" was considered the main influence factor of human activities.

© 2019 Published by Elsevier B.V.

1. Introduction

The Chinese Loess Plateau is an area subjected to serious soil erosion and water shortage (Shi and Shao, 2000; Zhao et al., 2013). Vegetation in the area is degraded due to serious soil and water loss and severe

* Corresponding authors.
E-mail addresses: fmli@lzu.edu.cn (F.-M. Li), yejsh@lzu.edu.cn (J.-S. Ye).

https://doi.org/10.1016/j.scitotenv.2019.01.022
0048-9697/© 2019 Published by Elsevier B.V.

human disturbances (Chen et al., 2001; Zhang et al., 2003). However, vegetation coverage has increased over recent decades probably due to the "Grain for Green Project," which was first implemented by the Chinese government in 1999 (Chen et al., 2015).

The factors that affect vegetation changes mainly include two types: climate change and human activities (Wang et al., 2015). The normalized difference vegetation index (NDVI) has been widely used in remote sensing of vegetation for decades (Defries and Townshend, 1994; Detsch et al., 2016; Huang et al., 2010; Liu et al., 2018; Townshend and Justice, 1986; Wang et al., 2003; Yang et al., 2005). NDVI shows sensitivity variations in response to global climate changes, and sensitivity to precipitation is particularly high in arid and semi-arid areas (Eklundh, 1998; Piao et al., 2004; Piao et al., 2003). Human activities also exert strong impacts on NDVI changes, which have been studied for a long time (Hilker et al., 2013; Li et al., 2017). For example, the "Grain for Green Project" has improved vegetation cover in hilly southern China (Wang et al., 2015) and the Loess Plateau (Zhou et al., 2012). Vegetation was also found to change due to the expansion of Mexico City (López et al., 2001).

It is well known policies could impact human activities greatly in the Loess Plateau (Lü et al., 2012). The "Grain for Green Project" clearly prohibits the exploitation of any land with slopes > 25° and recommends not to cultivate slopes between 15° and 25° (Lu et al., 2013; Uchida et al., 2005). Research also showed a significant upward trend in NDVI was found on slopes exceeding 15° in the Loess Plateau region (Zhang et al., 2013). Thus, we regarded slopes as an important factor to study human activities in this study.

Although numerous studies about the factors of climate change and human activities that induce NDVI changes have been conducted, research on quantifying the contribution of climate change and human activities to vegetation coverage was rare (Sun et al., 2015; Wang et al., 2015; Xie et al., 2016). Residual analysis is a common type of quantitative analysis that can be used to quantify the contribution of climate change by a quadratic equation between NDVI and climate factors (Li et al., 2017; Wang et al., 2015). However, the quadratic equation used in residual analysis must be adjusted before being applied to different periods or areas of the same region.

Vegetation index, such as NDVI and enhanced vegetation index, is a measure of the photosynthetic activity of terrestrial vegetation, and the photosynthetic activity of vegetation is affected by climate (Cabello et al., 2012; Myneni et al., 1997). Net primary productivity (NPP) is also affected by climate, and most NPP prediction models are based on climatic factors such as precipitation and temperature, and they have proven to be a practical tool to calculate primary productivity (Prince et al., 2009; Zhang et al., 2011). In addition, a strong relationship exists between NDVI and NPP (Ponce-Campos et al., 2013; Running et al., 2004; Ye et al., 2018); thus, they can be measured by each other in most kinds of land cover/land use types in the world (Scurlock et al., 1999; Turner et al., 2006). Therefore, NDVI and NPP can be estimated using climate data and NPP prediction models (Zhang et al., 2011).

Many NPP prediction models such as the Miami model and Thornthwaite Memorial model are extensively used worldwide (Grosso et al., 2008; Lieth, 1973; Lieth and Box, 1972; Zhang et al., 2011). However, no ready-made NPP prediction models are currently available for the Loess Plateau. As several studies have reported various relationships between NPP and NDVI in different land cover/land use types (Boelman et al., 2003; Santin-Janin et al., 2009), we should select an NPP model that is suitable for the grassland of the Loess Plateau.

Grassland, covering > 40% of the total area in the Loess Plateau, is one of the most important ecosystems in the region (Zhou et al., 2010). However, most of the grasslands are affected by human activities. This study aimed to (1) identify an NPP model that can be widely used in grassland of the Chinese Loess Plateau and apply it to quantify the contribution of climate change and (2) quantify the contribution of human activities using both actual NDVI and the contribution of climate change and then identify its impact factors.

2. Methods

2.1. Study region

The Chinese Loess Plateau, covering an area of 640,000 km^2, is one of the regions suffering the most serious soil erosion in the world. The climate is characterized by cold and dry winters and warm and wet summers. The mean annual air temperature is 14.0 °C in the southeast, and it decreases to 3.6 °C in the northwest during 1961–2009 (Li et al., 2010). The mean annual precipitation is >700 mm at the southeast and gradually decreases northward to only 100 mm in the northwest (Li et al., 2017). Grasslands cover an area of 265,484 ± 669 km^2 over 2000–2015, accounting for 41.48% ± 0.10% of the total area (Fig. 1).

In addition to the whole study region, we chose 10 prefecture level subregions where policies were carried out to varying degrees to analyze vegetation changes (Fig. 1b). Given that these prefecture level subregions have different populations (total population of 1,308,442–4,390,837 and rural population of 496,806–2,385,545 over 2000–2016) and topography (mean elevation of 1023.54–2782.83 m and slope of 1.77–16.53°), implementation of the policy may result in different changes in vegetation (Table 1). These prefecture level subregions also have different climatic conditions (mean precipitation of 282.66–613.42 mm over 2000–2016), so the spatial variations in vegetation changes should be analyzed in detail.

2.2. Data collection

The resolution of land use dataset of the Loess Plateau is 1 km as provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn). The grasslands of the Loess Plateau over 2000–2015 included high covered grassland with coverage > 50%, middle covered grassland with coverage range of 20%–50%, and low covered grassland with coverage range of 5%–20%.

Climate data (monthly precipitation and air temperature) at 112 stations within and around the Loess Plateau were obtained from the National Meteorological Information Center (http://data.cma.cn/). The spatial distribution of precipitation in the entire region was predicted using Kriging interpolation in ArcMap (version 10.0; ESRI, Redlands, CA, USA) from the climate data. Slope data were collected from Data Cloud of Chinese Academy of Sciences (http://www.csdb.cn/), which were obtained using images from the Shuttle Radar Topography Mission (SRTM) with a resolution of 90 m.

EOS-MODIS NDVI with 250 m resolution was obtained from LAADS DAAC (https://ladsweb.modaps.eosdis.nasa.gov/). The 16-day datasets were averaged to determine annual values. EOS-MODIS NDVI datasets did not include images during the first 49 days of 2000; three images in this period were replaced by images of the same period in 2001.

Biomass data were collected from 34 grassland sites of the Chinese Loess Plateau. These 34 sites were selected from nature grassland that was not disturbed by human activities. Among the 34 sites, 21 were collected from field sites whose samples were 60 m × 60 m (hereafter, field sites), and the other 13 sites were collected from the literature (hereafter, literature sites; Fig. 1). During 2013–2016, six 1 m^2 quadrats were chosen to extract aboveground biomass within each field site. The biomass data were also collected from five studies in the literature (Eerdengsubuda, 2013; Gao et al., 2017; Liang, 2015; Ren et al., 2017; Zhu et al., 2010).

2.3. Model selection

To calculate NPP and determine the extent it is affected by climate during 2000–2016, an NPP model widely used in the Loess Plateau was selected. Therefore, model selection was divided into two parts: acquisition of measured biomass data and selection and verification of the models.

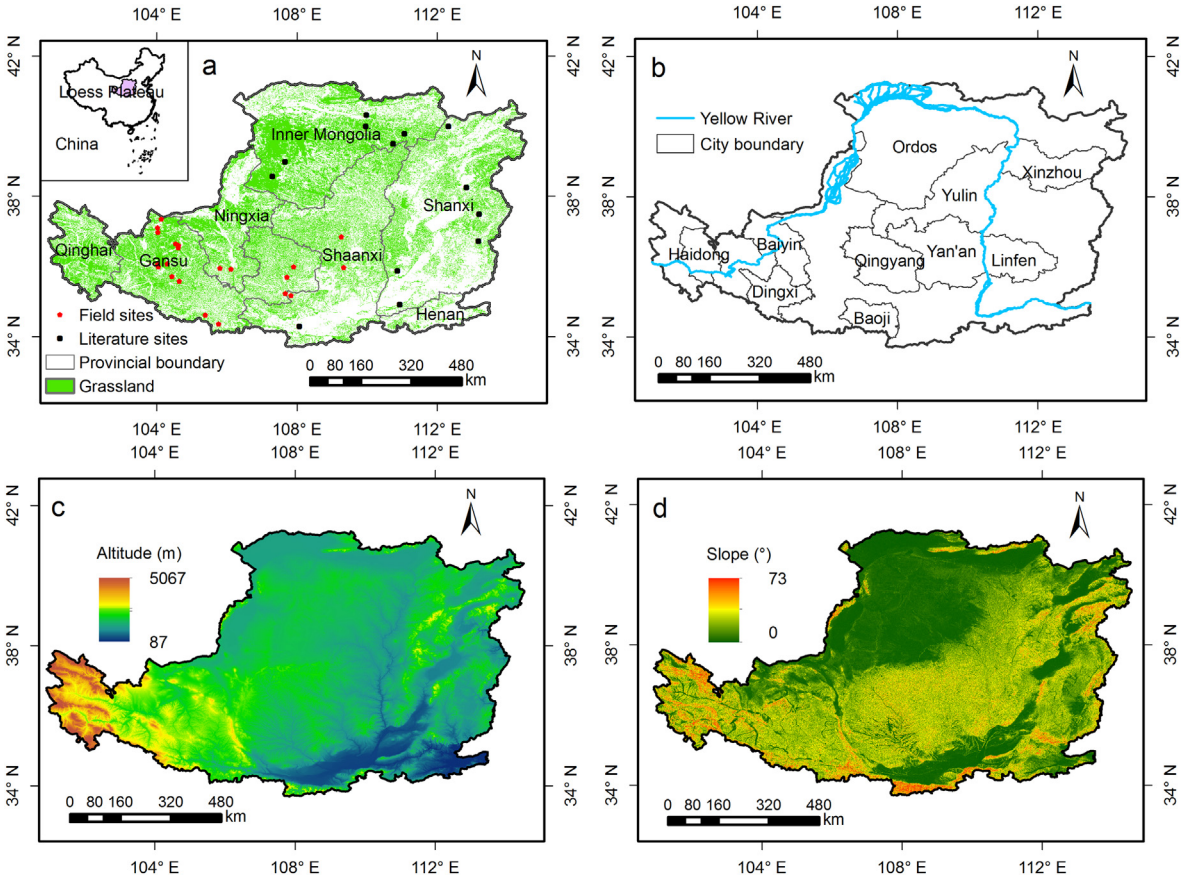


Fig. 1. Spatial patterns of topographical factors on the Chinese Loess Plateau. Location of grassland and field and literature sites (a), location of 10 prefecture level subregions (b), altitude (c), and slope (d).

Several models, such as the Miami model and the Thornthwaite Memorial model, have been used to calculate NPP worldwide (Lieth, 1973; Lieth and Box, 1972). The NCEAS model, which was an improvement from the Miami model, was also used to calculate NPP worldwide (Grosso et al., 2008). The Synthetic model, which was in accordance with the situation in China, was invented by Chinese researchers (Zhou and Zhang, 1995). Thus, these four models were chosen to verify and select an NPP model that could be widely used in grassland of the Chinese Loess Plateau. First, the Miami model was proposed by Lieth (1973), and it was the first global scale empirical model of terrestrial NPP:

$$\mathrm{NPPr} = 3000 \times \left[1 - \exp\left(-6.64 \times 10^{-4} \times \mathrm{MAP}\right)\right], \quad (1)$$

$$\mathrm{NPPt} = 3000/[1 + \exp(1.315 - 0.119 \times \mathrm{MAT})], \quad (2)$$

$$\mathrm{NPP} = \min(\mathrm{NPPr}, \mathrm{NPPt}), \quad (3)$$

where MAP is mean annual precipitation, and MAT is mean annual temperature.

Second, given that the NPP calculated by the Miami model was much higher than observation in some regions, the NCEAS model was proposed (Grosso et al., 2008) to improve it. The NCEAS model predicts lower NPP than the Miami model, particularly at high MAP values, and it is also widely used globally where the MAP range is 0–3000 mm. The NCEAS model is calculated as follows:

if non-tree,

Table 1
Description of the 10 prefecture level subregions, and their population, topography and precipitation over 2000–2016.

		Total population	Rural population	Area, km^2	Elevation, m	Slope, degree	Precipitation, mm
1	Haidong	1,703,359	1,139,408	13,044	2782.83	16.53	436.67
2	Baiyin	1,712,200	972,000	21,209	1856.59	8.70	282.66
3	Dingxi	2,770,700	2,018,200	19,609	2180.79	12.66	444.65
4	Qingyang	2,222,700	1,565,000	27,119	1443.22	12.69	518.87
5	Ordos	2,004,200	697,913	86,752	1322.77	1.77	303.90
6	Yulin	1,308,442	496,806	43,578	1232.19	7.16	465.16
7	Yan'an	2,377,760	1,568,062	37,037	1246.76	13.51	577.13
8	Baoji	3,856,270	1,827,542	18,117	1228.98	14.30	613.42
9	Linfen	4,390,837	2,385,545	20,275	1023.54	11.58	569.24
10	Xinzhou	3,114,394	1,773,950	25,472	1441.58	12.71	529.79

The population data according to Gansu Statistical Yearbook, Qinghai Statistical Yearbook, Shaanxi Statistical Yearbook, Shanxi Statistical Yearbook and Inner Mongolia Statistical Yearbook over 2000–2016.

$$\mathrm{ANPP} = 4000 \times \left[1 - \exp\left(-4.77 \times 10^{-5} \times \mathrm{MAP}\right)\right], \quad (4)$$

if tree, min[F(MAP), F(MAT)],

$$\text{where } \mathrm{F(MAP)} = 0.1665 \times \mathrm{MAP}^{1.185} / \exp(0.000414 \times \mathrm{MAP}), \quad (5)$$

$$\text{and } \mathrm{F(MAT)} = 3139/[1 + \exp(2.2 - 0.0307 \times \mathrm{MAT})], \quad (6)$$

ANPP is aboveground NPP. We focused on grassland, thus formula (4) was used.

Third, the Synthetic model proposed by Zhou and Zhang in 1995 was used to calculate NPP in accordance with annual precipitation and biomass temperature (Zhou and Zhang, 1995). The model was suitable for arid and semi-arid areas in China, and it is calculated as follows:

$$\mathrm{NPP} = \mathrm{RDI}^2 \times \frac{r\left(1 + \mathrm{RDI} + \mathrm{RDI}^2\right)}{(1 + \mathrm{RDI})\left(1 + \mathrm{RDI}^2\right)} \times \exp\left(-\sqrt{9.87 + 6.25\mathrm{RDI}}\right) \times 100, \quad (7)$$

$$\mathrm{RDI} = \left(0.629 + 0.237 \times \mathrm{PER} - 0.00313 \times \mathrm{PER}^2\right)^2, \quad (8)$$

$$\mathrm{PER} = 58.931 \times \mathrm{BT}/r, \quad (9)$$

where PER is the potential evaporation, BT is the monthly mean biomass temperature for temperatures between 0 °C and 30 °C, and r is the annual precipitation (mm).

Fourth, the Thornthwaite Memorial model was proposed by Lieth and Box (1972). This model is based on the data used in the Miami model, and its predictor variable is changed to potential evaporation instead of MAP or MAT. The Thornthwaite Memorial model is calculated as follows:

$$\mathrm{NPP} = 3000 \times \{1 - \exp[-0.0009695(\mathrm{ev} - 20)]\}, \quad (10)$$

where ev is mean annual potential evaporation.

Linear regression analysis was applied to assess the relationship between observed biomass and NPP from the four models. Akaike Information Criterion (AIC) was used for model selection. The best model that was suitable for the grassland of the Loess Plateau was identified. Finally, we obtained the NDVI affected by climate through a regression of the calculated NPP by the best model and the annual NDVI calculated from MODIS data.

2.4. Attributing vegetation change

Changes in NDVI of grassland on the Chinese Loess Plateau could be categorized into two parts. One was NDVI affected by climate change ($\mathrm{NDVI_{climate}}$), and the other part was NDVI affected by human activities ($\mathrm{NDVI_{human}}$). Considering that $\mathrm{NPP_{climate}}$ was calculated by the NPP model using the climate data, and $\mathrm{NDVI_{climate}}$ was calculated by $\mathrm{NPP_{climate}}$ and the regression equation, $\mathrm{NDVI_{human}}$ was calculated as follows:

$$\mathrm{NDVI_{human}} = \mathrm{NDVI_{actual}} - \mathrm{NDVI_{climate}}, \quad (11)$$

where $\mathrm{NDVI_{actual}}$ is the mean annual NDVI from MODIS images, and it is affected by both climate and human activities.

The research period could also be divided into two stages. The first stage was the early stage of "Grain for Green Project" implementation (2000–2007, t1), and the second was the mature stage of implementation (2009–2016, t2). On the basis of Eq. (11), $\mathrm{NDVI_{human}}$ in the two stages was calculated as follows:

$$\mathrm{NDVI_{human,t1}} = \mathrm{NDVI_{actual,t1}} - \mathrm{NDVI_{climate,t1}}, \quad (12)$$

$$\mathrm{NDVI_{human,t2}} = \mathrm{NDVI_{actual,t2}} - \mathrm{NDVI_{climate,t2}}, \quad (13)$$

The actual NDVI changes ($\Delta\mathrm{NDVI_{actual}}$) in the two stages t1 and t2 were calculated as follows:

$$\Delta\mathrm{NDVI_{actual}} = \mathrm{NDVI_{actual,t2}} - \mathrm{NDVI_{actual,t1}}, \quad (14)$$

$\Delta\mathrm{NDVI_{actual}}$ could be decomposed into those induced by climate change $\Delta\mathrm{NDVI_{climate}}$ and human activities $\Delta\mathrm{NDVI_{human}}$. Furthermore, $\Delta\mathrm{NDVI_{human}}$ and $\Delta\mathrm{NDVI_{climate}}$ in the two stages could be calculated as follows:

$$\Delta\mathrm{NDVI_{human}} = \mathrm{NDVI_{human,t2}} - \mathrm{NDVI_{human,t1}}, \quad (15)$$

$$\Delta\mathrm{NDVI_{climate}} = \mathrm{NDVI_{climate,t2}} - \mathrm{NDVI_{climate,t1}}, \quad (16)$$

During the study period, we conducted a quantitative analysis of the contributions of human activities and climate change to NDVI changes through Eqs. (14)–(16).

The relationships between $\mathrm{NDVI_{human}}$ change and impact factors (such as slope, elevation, precipitation, total population, and rural population) were analyzed by SPSS 19.0. One-way ANOVA was used to assess differences in NDVI among different slopes.

3. Results

3.1. Model selection

Significant relationships between biomass and NPP were found in all the four models (Fig. 2). The NPP calculated by the NCEAS model ($\mathrm{NPP_{NCEAS}}$) had the highest correlation with the observed biomass ($R^2 = 0.5297$, Fig. 2a), whereas the Synthetic model demonstrated the lowest correlation ($R^2 = 0.3792$, Fig. 2c); the AIC of the NCEAS model was the smallest (AIC = 555.53) compared with those of the other models. Considering both R^2 and AIC, the NCEAS model was chosen to calculate the NDVI affected by climate change.

A statistically significant relationship was found ($p < 0.001$) between $\mathrm{NDVI_{actual}}$ and $\mathrm{NPP_{NCEAS}}$ in 21 field sites during 2014–2016 (Fig. 3). Given that the NDVI of the 21 field sites was only affected by climate, the strong correlation implied that $\mathrm{NDVI_{climate}}$ of the grassland can be calculated by $\mathrm{NPP_{NCEAS}}$ in the Chinese Loess Plateau.

3.2. NDVI change in the Chinese Loess Plateau

Our results suggested that $\mathrm{NDVI_{actual}}$ increased significantly ($p < 0.001$) over 2000–2016 in the Chinese Loess Plateau (Fig. 4a). Compared with the starting stage (2000–2007, t1), the overall NDVI in grassland of the Chinese Loess Plateau increased by 14.16% in the later stage (2009–2016, t2). However, the change in NDVI was spatially nonuniform (Fig. 4b). In ten prefecture level subregions, $\Delta\mathrm{NDVI_{actual}}$ of western Ordos and northern Baiyin decreased, whereas $\Delta\mathrm{NDVI_{actual}}$ increased in Yulin, Yan'an, and western Linfen.

3.3. Qualitative analysis of NDVI change

3.3.1. NDVI change affected by climate change and human activities

$\Delta\mathrm{NDVI_{climate}}$ between two study stages was 0.0208 (i.e., 27.19% increase) in the grassland. The $\Delta\mathrm{NDVI_{climate}}$ values increased in all the northern parts of the Chinese Loess Plateau but decreased in some of the southern areas of the Loess Plateau. In the ten prefecture level subregions, $\Delta\mathrm{NDVI_{climate}}$ of Baiyin City in the southwest of the Loess Plateau

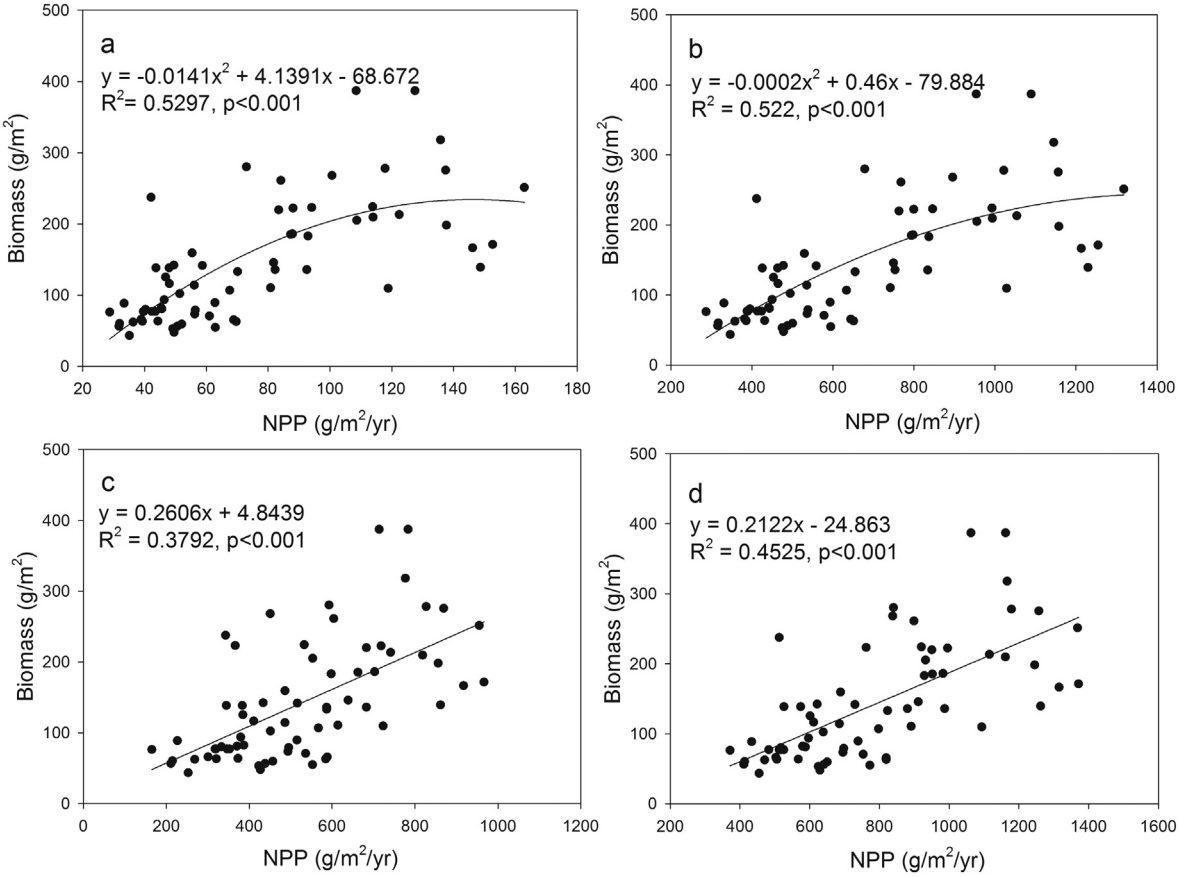


Fig. 2. Relationships between observed biomass and net primary productivity (NPP) calculated by four models. a: NCEAS model, b: Miami model, c: Synthetic model, d: Thornthwaite Memorial model.

was the smallest, and the value of Yulin City in the north was largest (Fig. 5a).

The distribution of $\Delta NDVI_{human}$ was opposite to that of $\Delta NDVI_{climate}$ (Fig. 5b). The $\Delta NDVI_{human}$ values decreased in the northwest but increased in the south of the Loess Plateau. In the ten prefecture level subregions, the $\Delta NDVI_{human}$ value of Ordos decreased, whereas those of the other nine subregions increased. Between two study stages, the $\Delta NDVI_{climate}$ and $\Delta NDVI_{human}$ values both increased in Yulin and Yan'an.

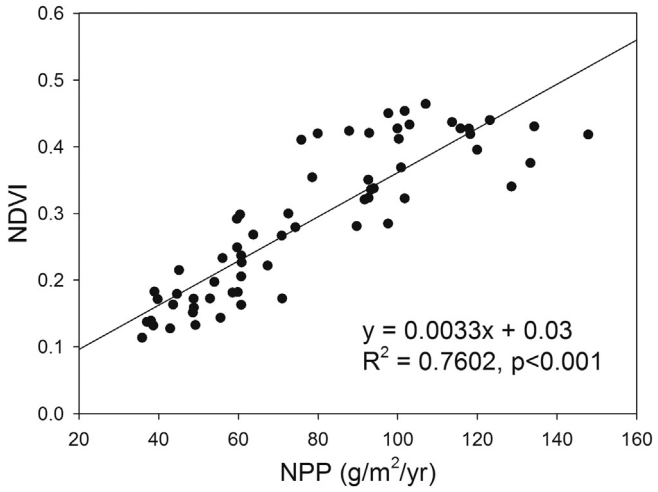


Fig. 3. Relationship between annual normalized difference vegetation index (NDVI) calculated by MODIS ($NDVI_{actual}$) and NPP calculated by the NCEAS model for the 21 field sites.

3.3.2. Qualitative analysis

Over the whole Loess Plateau, climate change played a more important role in NDVI change than human activities (Table 2). The per pixel $\Delta NDVI_{actual}$ value increased by 0.0361; human activities and climate change contributed to the 42.35% and 57.65% increase in NDVI in the Loess Plateau, respectively. Given the involvement of different topographical factors and social factors, the contribution of human activities and climate change varied in the ten prefecture level subregions. Human activities contributed to a 115.46% increase in NDVI in Dingxi but a 25.69% decrease in NDVI in Ordos. The highest $NDVI_{climate}$ change was 0.0498 in Yulin, and the lowest $NDVI_{climate}$ change was −0.0053 in Dingxi.

3.4. Impact of human activities

Regression analysis revealed a statistically significant relationship between $\Delta NDVI_{human}$ and slope (Table 3, $p < 0.01$). However, no statistically significant relationship was found between $\Delta NDVI_{human}$ and other factors such as precipitation, total population, rural population, and elevation ($p > 0.05$).

Compared with the starting stage (2000–2007), NDVI was lower in land with the slope of 0°–2° and higher with other slopes (Fig. 6). The trend of $\Delta NDVI_{human}$ increased with rising slope in the range of 0°–25° and decreased with slope >25° (Fig. 6). $\Delta NDVI_{human}$ was statistically significant among all slopes. The land area with slopes of 6°–15° was the

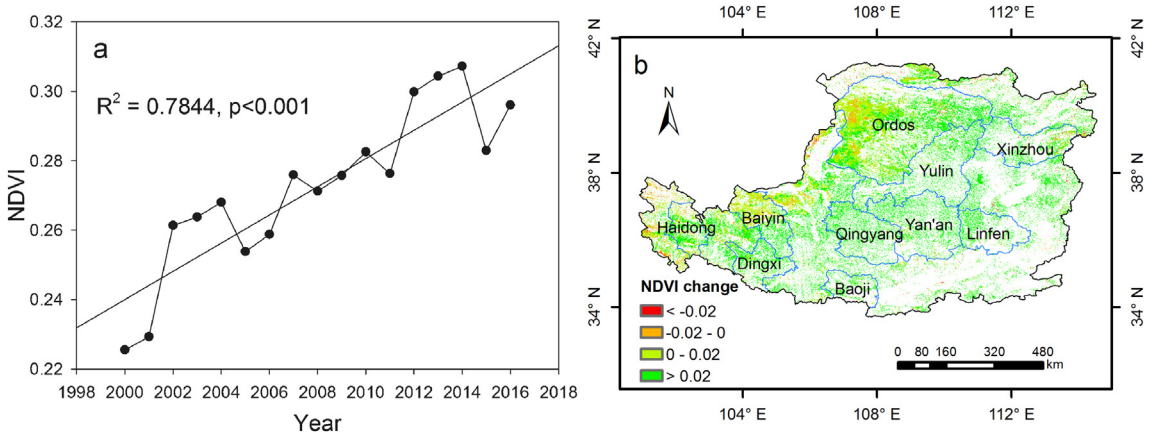


Fig. 4. $NDVI_{actual}$ change during the study period (2000–2016) in grassland of the Chinese Loess Plateau (a). $\Delta NDVI_{actual}$ ($NDVI_{actual,\ t2}$ minus $NDVI_{actual,\ t1}$) of grassland in the Chinese Loess Plateau (b).

largest (87,960 km^2) on the Loess Plateau, and it contributed to a 58.39% increase in $\Delta NDVI_{human}$.

4. Discussion

4.1. Model selection and calibration

In the present study, we introduced a new method that used the NPP model and relationship between NPP and NDVI to quantitatively and spatially distinguish between the ΔNDVI affected by climate change and human activities. The key step of the new method was to estimate the extent of NDVI that was affected by climate, and $NDVI_{climate}$ was calculated from $NPP_{climate}$ (Fig. 3). Furthermore, $NPP_{climate}$ was calculated from climate data using the NPP model. Therefore, selecting a model to estimate the NPP affected by climate is crucial.

NPP models have been successfully used to calculate the contributions of climate change and human activities (Zhang et al., 2011). As a dataset, NPP can be used in most kinds of land cover/land use types including grassland (Kinyamario, 1996; Scurlock et al., 1999; Turner et al., 2006).

Major differences were found in parameters of NPP models across different regions (Liu et al., 2008). These NPP models could be calibrated and verified in different regions, and we should choose a model that is most suitable for the grassland in the Chinese Loess Plateau. According to the relationship of the biomass observations and NPP, we found that the NCEAS was the most suitable model for the grassland of the Loess Plateau (Fig. 2). Irisarri et al. (2012) showed that the NCEAS model was a generalist in predicting NPP in grassland ecosystems, which was consistent with our results. Given that the NPP calculated by the Miami model was too high in some areas, particularly in high MAP areas, the NCEAS model was established via the Miami model (Grosso et al., 2008).

NDVI can be a proxy of vegetation productivity in many ecosystems, such as grassland, agro-ecosystem, at various scales worldwide (Running, 1990; Santin-Janin et al., 2009). However, most studies showed that NDVI can only represent the productivity of single land use type (Boelman et al., 2003; Santin-Janin et al., 2009). Different relationships were found between NPP and NDVI in different vegetation types, and NDVI could effectively monitor and manage the different land use types in the ecosystems and their productivity (Jiang et al., 2011). Our results showed that NDVI had a high connection with NPP in the grassland, and this finding was consistent with results of previous studies (Hermance et al., 2015; Santin-Janin et al., 2009).

4.2. Qualitative analysis of NDVI change

The "Grain for Green project" increased vegetation coverage on the Loess Plateau (Chen et al., 2015; Fu et al., 2011; Wang et al., 2011; Xin et al., 2008). Our results showed that the overall NDVI also increased during 2000–2016 in the grassland of the Loess Plateau.

The temporal and spatial variations in ΔNDVI differed in the Loess Plateau due to changes in climate and human activities (Ding et al.,

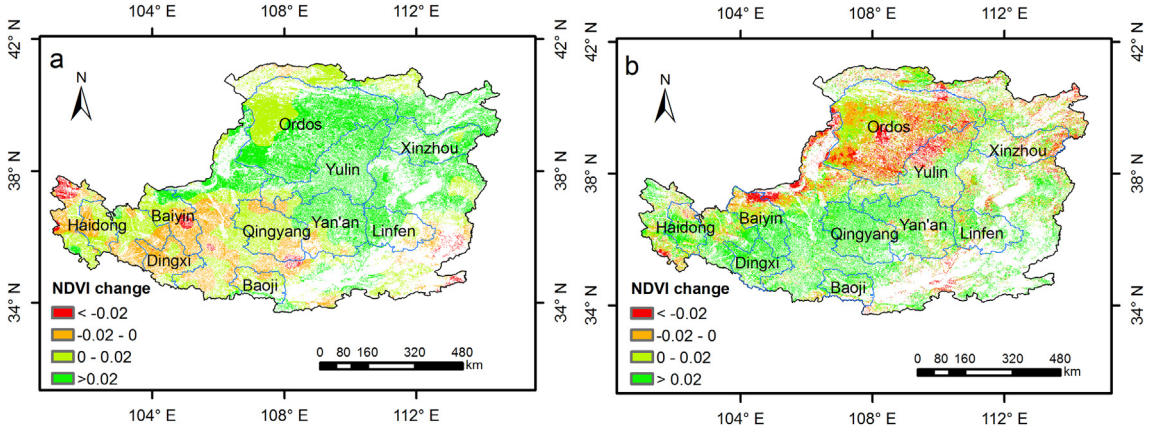


Fig. 5. $\Delta NDVI_{climate}$ ($NDVI_{climate,\ t2}$ minus $NDVI_{climate,\ t1}$) of grassland in the Chinese Loess Plateau (a). $\Delta NDVI_{human}$ ($NDVI_{human,\ t2}$ minus $NDVI_{human,\ t1}$) of grassland in the Chinese Loess Plateau (b).

Table 2
Qualitative analysis of NDVI changes in the Chinese Loess Plateau (CLP).

		$\Delta NDVI_{climate}$	$\Delta NDVI_{human}$	$\Delta NDVI_{actual}$	$\Delta NDVI_{climate}$%	$\Delta NDVI_{human}$%
	CLP	0.0208	0.0153	0.0361	57.65%	42.35%
1	Haidong	0.0012	0.0260	0.0272	4.59%	95.41%
2	Baiyin	0.0023	0.0191	0.0214	10.64%	89.36%
3	Dingxi	−0.0053	0.0394	0.0341	−15.46%	115.46%
4	Qingyang	0.0040	0.0445	0.0485	8.27%	91.73%
5	Ordos	0.0309	−0.0063	0.0246	125.69%	−25.69%
6	Yulin	0.0498	0.0066	0.0564	88.26%	11.74%
7	Yan'an	0.0277	0.0365	0.0642	43.20%	56.80%
8	Baoji	0.0073	0.0360	0.0433	16.76%	83.24%
9	Linfen	0.0306	0.0256	0.0562	54.44%	45.56%
10	Xinzhou	0.0346	0.0068	0.0414	83.67%	16.33%

2016; Li et al., 2017; Ning et al., 2015). For example, NDVI significantly increased in the northern Loess Plateau including eastern Ordos, northern Yulin, and western Xinzhou because of slightly increased precipitation and some positive human activities (Ning et al., 2015). However, studies showed that NDVI in the northwestern Loess Plateau reduced in recent years (Li et al., 2017). The present study yielded similar results. Thus, NDVI in the Loess Plateau generally increased, but it also exhibited a tendency to decrease in some parts of the region.

Desertification is one of the reasons for the decline in NDVI, and the area with an extreme degree of desertification expanded in the northwestern Loess Plateau mainly along the Yellow River of Ningxia and Gansu Provinces (Abla et al., 2015). The desertification of the northwestern Loess Plateau is mainly caused by human activities (Liang and Yang, 2016). Long-term heavy grazing may cause the grassland to turn into bare land, and excessive agriculture practice may also result in regional desertification (Liang and Yang, 2016; Zhao et al., 2005). Therefore, desertification caused by heavy grazing and excessive agriculture may be the cause of $NDVI_{human}$ reduction in grassland of the northwestern Loess Plateau. In contrast to the northwestern Loess Plateau, $NDVI_{human}$ increased in other regions. Since the "Grain for Green Project" was implemented in 1999, numerous studies have shown reduced impacts of human activities on vegetation destruction (Li et al., 2017; Wang et al., 2015). Thus, the increased $NDVI_{human}$ values of grassland were caused by the "Grain for Green Project." However, different results were obtained for various regions (Table 2). The mechanism underlying human activity changes in different regions remains unknown.

4.3. Impact of human activities

Many factors such as population density, policy, and topography affect human activities (Li et al., 2017; Wang et al., 2015). However, slope was the only significant factor that influenced $\Delta NDVI_{human}$ changes in this study (Table 3).

In line with the anticipated results of the "Grain for Green Project", the highest $\Delta NDVI_{human}$ value was in the range of 15°–25° in this study (Fig. 6). This result was similar to that reported in other studies and consistent with the "Grain for Green Project" regulations (Lu et al., 2013; Uchida et al., 2005; Zhang et al., 2013). The low $\Delta NDVI_{human}$ value in the range of 0°–2° may be caused by desertification in the northwestern Loess Plateau where slope is the smallest (Figs. 1d, 5b, and 6). Human activities are more difficult in the area with slope > 25°, and thus the difference between two stages of the $NDVI_{human}$ values is very small. Our results suggested that the region with a slope in the range of 6°–15° contributed most to NDVI affected by human activities because the land area was the largest in the Loess Plateau. Given that NDVI changes in different slopes were caused by the "Grain for Green Project," the policy was an important factor affecting human activities.

Table 3
Relationships between $\Delta NDVI_{human}$ ($NDVI_{human,\ t2}$ minus $NDVI_{human,\ t1}$) and population density, topography, precipitation.

Factors	Relational expression	R^2	p
Total population density, p/km^2	$\Delta NDVI_{human} = 0.0001x + 0.0107$	0.2181	>0.05
Rural population density, p/km^2	$\Delta NDVI_{human} = 0.0003x + 0.0068$	0.3494	>0.05
Elevation, m	$\Delta NDVI_{human} = 0.000006x + 0.0139$	0.0321	>0.05
Slope, °	$\Delta NDVI_{human} = 0.003x - 0.0097$	0.5617	<0.05
Precipitation, mm	$\Delta NDVI_{human} = 0.00008x - 0.0151$	0.2854	>0.05

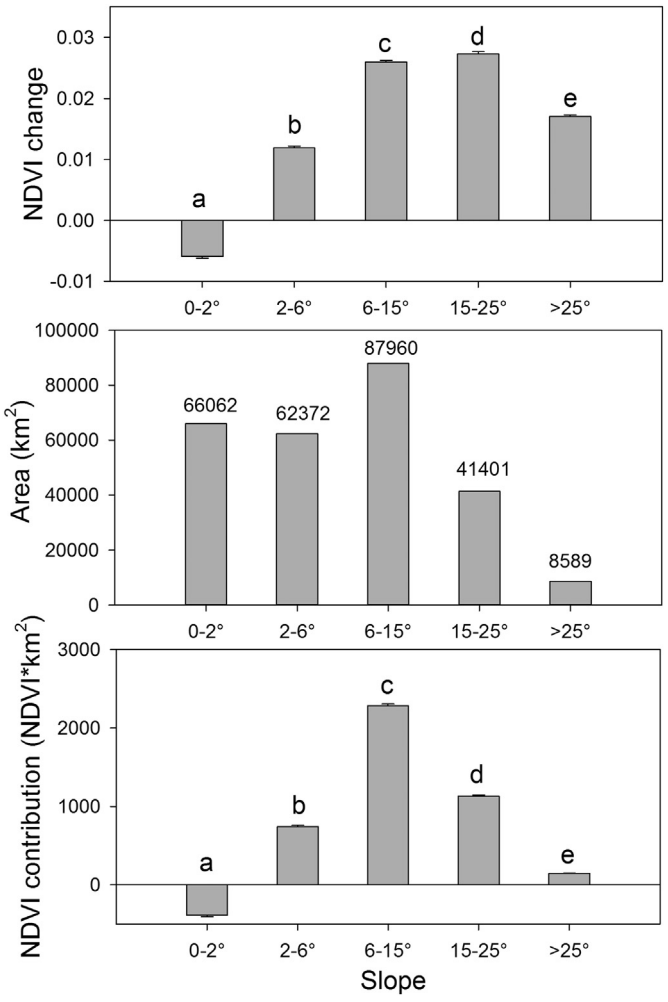


Fig. 6. $\Delta NDVI_{human}$ ($NDVI_{human,\ t2}$ minus $NDVI_{human,\ t1}$), land area, and NDVI (per pixel change multiplied by land areas) across different slopes in the Loess Plateau.

5. Conclusions

In this study, $NDVI_{climate}$ and $NDVI_{human}$ in grassland of the Loess Plateau were calculated respectively. Compared with the starting stage (2000–2007), the mean NDVI of the later stage (2009–2016) increased by 14.16% in grassland of the Chinese Loess Plateau. Human activities and climate change contributed to 42.35% and 57.65% of the increase in NDVI, respectively. However, these values were spatially variable, and human activities contributed to −25.69% to 115.46% increase in NDVI in ten prefecture level subregions. Analysis of various factors revealed that the slopes restored by the "Grain for Green Project" was the main factor of NDVI change by human activities.

Acknowledgement

This study was supported by the National Natural Science Foundation of China (NSFC31570467), the Fundamental Research Funds for the Central Universities (lzujbky-2015-570 ct02), and project of State Key Laboratory of Grassland Agro-ecosystems of Lanzhou University (SKLGAE201511).

References

Abla, M., Zhang, X., Chen, L., Lin, P., Sun, Y., 2015. Spatial-temporal distribution of desertification on the Loess Plateau using the GIMMS NDVI data. Sci. Soil Water Conserv. 13, 24–31. https://doi.org/10.3969/j.issn.1672-3007.2015.03.004.

Boelman, N.T., Stieglitz, M., Rueth, H.M., Sommerkorn, M., Griffin, K.L., Shaver, G.R., Gamon, J.A., 2003. Response of NDVI, biomass, and ecosystem gas exchange to long-term warming and fertilization in wet sedge tundra. Oecologia 135, 414–421. https://doi.org/10.1007/s00442-003-1198-3.

Cabello, J., Alcaraz-Segura, D., Ferrero, R., Castro, A.J., Liras, E., 2012. The role of vegetation and lithology in the spatial and inter-annual response of EVI to climate in drylands of Southeastern Spain. J. Arid Environ. 79, 76–83. https://doi.org/10.1016/j.jaridenv.2011.12.006.

Chen, L., Wang, J., Fu, B., Qiu, Y., 2001. Land-use change in a small catchment of northern Loess Plateau, China. Agric. Ecosyst. Environ. 86, 163–172. https://doi.org/10.1016/S0167-8809(00)00271-1.

Chen, Y., Wang, K., Lin, Y., Shi, W., Song, Y., He, X., 2015. Balancing green and grain trade. Nat. Geosci. 8, 739–741. https://doi.org/10.1038/ngeo2544.

Defries, R., Townshend, J., 1994. NDVI-derived land cover classification at global scales. Int. J. Remote Sens. 15, 3567–3586. https://doi.org/10.1080/01431169408954345.

Detsch, F., Otte, I., Appelhans, T., Hemp, A., Nauss, T., 2016. Seasonal and long-term vegetation dynamics from 1-km GIMMS-based NDVI time series at Mt. Kilimanjaro, Tanzania. Remote Sens. Environ. 178, 70–83. https://doi.org/10.1016/j.rse.2016.03.007.

Ding, Y., Zheng, X., Zhao, K., Xin, X., Liu, H., 2016. Quantifying the impact of NDVIsoil determination methods and NDVIsoil variability on the estimation of fractional vegetation cover in Northeast China. Remote Sens. 8, 29. https://doi.org/10.3390/rs8010029.

Eerdengsubuda, 2013. Comparison Research on Carbon Storage of 3 Vegetations in Inner Mongolia Ordos. Inner Mongolia Argriculture University.

Eklundh, L., 1998. Estimating relations between AVHRR NDVI and rainfall in East Africa at 10-day and monthly time scales. Int. J. Remote Sens. 19, 563–570. https://doi.org/10.1080/014311698216198.

Fu, B., Liu, Y., Lü, Y., He, C., Zeng, Y., Wu, B., 2011. Assessing the soil erosion control service of ecosystems change in the Loess Plateau of China. Ecol. Complex. 8, 284–293. https://doi.org/10.1016/j.ecocom.2011.07.003.

Gao, L., Zhu, F., Yan, Z., Wang, Y., Hou, X., Dai, Y., 2017. Effects of grazing on plant biomass and the carbon density of vegetation and soil in the Artemisia ordosica shrubland of the Ordos Plateau. Acta Ecol. Sin. 37, 3074–3083.

Grosso, S.D., Parton, W., Stohlgren, T., et al., 2008. Global potential net primary production predicted from vegetation class, precipitation, and temperature. Ecology 91, 923–925. https://doi.org/10.1890/07-0850.1.

Hermance, J.F., Augustine, D.J., Derner, J.D., 2015. Quantifying characteristic growth dynamics in a semi-arid grassland ecosystem by predicting short-term NDVI phenology from daily rainfall: a simple four parameter coupled-reservoir model. Int. J. Remote Sens. 36, 5637–5663. https://doi.org/10.1080/01431161.2015.1103916.

Hilker, T., Natsagdorj, E., Waring, R.H., Lyapustin, A., Wang, Y., 2013. Satellite observed widespread decline in Mongolian grasslands largely due to overgrazing. Glob. Chang. Biol. 20, 418–428. https://doi.org/10.1111/gcb.12365.

Huang, Q., Zhang, L., Wu, W., Li, D., 2010. MODIS-NDVI-Based crop growth monitoring in China Agriculture Remote Sensing Monitoring System. IITA International Conference on Geoscience & Remote Sensing (pp Page).

Irisarri, J.G.N., Oesterheld, M., Paruelo, J.M., Texeira, M.A., 2012. Patterns and controls of above-ground net primary production in meadows of Patagonia. A remote sensing approach. J. Veg. Sci. 23, 114–126. https://doi.org/10.1111/j.1654-1103.2011.01326.x.

Jiang, R., Li, X., Zhu, Y., Zhang, Z., 2011. Spatial-temporal variation of NPP and NDVI correlation in wetland of Yellow River Delta based on MODIS data. Acta Ecol. Sin. 31, 6708–6716.

Kinyamario, J.I., 1996. NPP Grassland: Nairobi, Kenya, 1984–1994. University of Nairobi Digital Repository.

Li, Z., Zheng, F.L., Liu, W.Z., Flanagan, D.C., 2010. Spatial distribution and temporal trends of extreme temperature and precipitation events on the Loess Plateau of China during 1961–2007. Quat. Int. 226, 92–100. https://doi.org/10.1016/j.quaint.2010.03.003.

Li, J., Peng, S., Li, Z., 2017. Detecting and attributing vegetation changes on China's Loess Plateau. Agric. For. Meteorol. 247, 260–270. https://doi.org/10.1016/j.agrformet.2017.08.005.

Liang, W., 2015. The Study on Simple Estimation Method of Aboveground Biomass of Grassland. Northwest A&F University.

Liang, P., Yang, X., 2016. Landscape spatial patterns in the Maowusu (Mu Us) Sandy Land, northern China and their impact factors. Catena 145, 321–333. https://doi.org/10.1016/j.catena.2016.06.023.

Lieth, H., 1973. Primary production: terrestrial ecosystems. Hum. Ecol. 1, 303–332. https://doi.org/10.1007/BF01536729.

Lieth, H., Box, E.O., 1972. Evapotranspiration and primary productivity: CW Thornthwaite memorial model. Publ. Climatol. 25, 37–46.

Liu, S., Anderson, P., Zhou, G., et al., 2008. Resolving model parameter values from carbon and nitrogen stock measurements in a wide range of tropical mature forests using nonlinear inversion and regression trees. Ecol. Model. 219, 327–341. https://doi.org/10.1016/j.ecolmodel.2008.07.025.

Liu, L., Yang, X., Zhou, H., et al., 2018. Evaluating the utility of solar-induced chlorophyll fluorescence for drought monitoring by comparison with NDVI derived from wheat canopy. Sci. Total Environ. 625, 1208. https://doi.org/10.1016/j.scitotenv.2017.12.268.

López, E., Bocco, G., Mendoza, M., Duhau, E., 2001. Predicting land-cover and land-use change in the urban fringe: a case in Morelia city, Mexico. Landsc. Urban Plan. 55, 271–285. https://doi.org/10.1016/s0169-2046(01)00160-8.

Lü, Y., Fu, B., Feng, X., et al., 2012. A policy-driven large scale ecological restoration: quantifying ecosystem services changes in the Loess Plateau of China. PLoS One 7, e31782. https://doi.org/10.1371/journal.pone.0031782.

Lu, Q., Xu, B., Liang, F., Gao, Z., Ning, J., 2013. Influences of the Grain-for-Green project on grain security in southern China. Ecol. Indic. 34, 616–622. https://doi.org/10.1016/j.ecolind.2013.06.026.

Myneni, R.B., Keeling, C.D., Tucker, C.J., Asrar, G., Nemani, R.R., 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. Nature 386, 698–702. https://doi.org/10.1038/386698a0.

Ning, T., Liu, W., Lin, W., Song, X., 2015. NDVI variation and its responses to climate change on the northern Loess Plateau of China from 1998 to 2012. Adv. Meteorol. 2015, 1–10. https://doi.org/10.1155/2015/725427.

Piao, S., Fang, J., Zhou, L., et al., 2003. Interannual variations of monthly and seasonal normalized difference vegetation index (NDVI) in China from 1982 to 1999. J. Geophys. Res. Atmos. 108, 4401–4413. https://doi.org/10.1029/2002jd002848.

Piao, S., Fang, J., Ji, W., Guo, Q., Ke, J., Tao, S., Woods, K., 2004. Variation in a satellite-based vegetation index in relation to climate in China. J. Veg. Sci. 15, 219–226. https://doi.org/10.1658/1100-9233(2004)015[0219:viasvi]2.0.co;2.

Ponce-Campos, G.E., Moran, M.S., Huete, A., et al., 2013. Ecosystem resilience despite large-scale altered hydroclimatic conditions. Nature 494, 349–352. https://doi.org/10.1038/nature11836.

Prince, S.D., Beckerreshef, I., Rishmawi, K., 2009. Detection and mapping of long-term land degradation using local net production scaling: application to Zimbabwe. Remote Sens. Environ. 113, 1046–1057. https://doi.org/10.1016/j.rse.2009.01.016.

Ren, M., Tan, Z., Zhang, Z., Gao, Y., Zhao, X., Ren, G., Su, Z., 2017. Spatial distribution characteristics of biomass in four main types of rangeland in Shanxi. Pratacultural Sci. 34, 2366–2377.

Running, S.W., 1990. Estimating terrestrial primary productivity by combining remote sensing and ecosystem simulation. Remote Sens. Biosph. Functioning, 65–86 https://doi.org/10.1007/978-1-4612-3302-2_4.

Running, S.W., Nemani, R.R., Heinsch, F.A., Zhao, M., Reeves, M., Hashimoto, H., 2004. A continuous satellite-derived measure of global terrestrial primary production. Bioscience 54, 547–560. https://doi.org/10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2.

Santin-Janin, H., Garel, M., Chapuis, J.L., Pontier, D., 2009. Assessing the performance of NDVI as a proxy for plant biomass using non-linear models: a case study on the Kerguelen archipelago. Polar Biol. 32, 861–871. https://doi.org/10.1007/s00300-009-0586-5.

Scurlock, J.M.O., Cramer, W., Olson, R.J., Parton, W.J., Prince, S.D., 1999. Terrestrial NPP: toward a consistent data set for global model evaluation. Ecol. Appl. 9, 913–919. https://doi.org/10.2307/2641338.

Shi, H., Shao, M.G., 2000. Soil and water loss from the Loess Plateau in China. J. Arid Environ. 45, 9–20. https://doi.org/10.1006/jare.1999.0618.

Sun, W., Song, X., Mu, X., Gao, P., Wang, F., Zhao, G., 2015. Spatiotemporal vegetation cover variations associated with climate change and ecological restoration in the Loess Plateau. Agric. For. Meteorol. 209–210, 87–99. https://doi.org/10.1016/j.agrformet.2015.05.002.

Townshend, J.R.G., Justice, C.O., 1986. Analysis of the dynamics of African vegetation using the normalized difference vegetation index. Int. J. Remote Sens. 7, 1435–1445. https://doi.org/10.1080/01431168608948946.

Turner, D.P., Ritts, W.D., Cohen, W.B., et al., 2006. Evaluation of MODIS NPP and GPP products across multiple biomes. Remote Sens. Environ. 102, 282–292. https://doi.org/10.1016/j.rse.2006.02.017.

Uchida, E., Xu, J., Rozelle, S., 2005. Grain for green: cost-effectiveness and sustainability of China's Conservation Set-Aside Program. Land Econ. 81, 247–264. https://doi.org/10.3368/le.81.2.247.

Wang, J., Rich, P., Price, K., 2003. Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int. J. Remote Sens. 24, 2345–2364. https://doi.org/10.1080/01431160210154812.

Wang, Y., Fu, B., Lü, Y., Chen, L., 2011. Effects of vegetation restoration on soil organic carbon sequestration at multiple scales in semi-arid Loess Plateau, China. Catena 85, 58–66. https://doi.org/10.1016/j.catena.2010.12.003.

Wang, J., Wang, K., Zhang, M., Zhang, C., 2015. Impacts of climate change and human activities on vegetation cover in hilly southern China. Ecol. Eng. 81, 451–461. https://doi.org/10.1016/j.ecoleng.2015.04.022.

Xie, B., Jia, X., Qin, Z., Shen, J., Chang, Q., 2016. Vegetation dynamics and climate change on the Loess Plateau, China: 1982–2011. Reg. Environ. Chang. 16, 1–12. https://doi.org/10.1007/s10113-015-0881-3.

Xin, Z.B., Xu, J.X., Wei, Z., 2008. Spatiotemporal variations of vegetation cover on the Chinese Loess Plateau (1981–2006): impacts of climate changes and human activities. Sci. China Earth Sci. 51, 67–78. https://doi.org/10.1007/s11430-007-0137-2.

Yang, J., Ding, Y., Chen, R., 2005. NDVI reflection of alpine vegetation changes in the source regions of the Yangtze and Yellow rivers. Acta Geograph. Sin. 60, 467–478.

Ye, J.S., Pei, J.Y., Fang, C., 2018. Under which climate and soil conditions the plant productivity-precipitation relationship is linear or nonlinear? Sci. Total Environ. 616, 1174–1180. https://doi.org/10.1016/j.scitotenv.2017.10.203.

Zhang, H., Wang, Y.P., Gao, P.C., Sun, P.Y., 2003. Research on mechanism about forming dry layer of slope land and way of supplying water on Loess Plateau. J. Soil Water Conserv. 3, 162–164. https://doi.org/10.3321/j.issn:1009-2242.2003.03.046.

Zhang, C., Wang, X., Li, J., Hua, T., 2011. Roles of climate changes and human interventions in land degradation: a case study by net primary productivity analysis in China's Shiyanghe Basin. Environ. Earth Sci. 64, 2183–2193. https://doi.org/10.1007/s12665-011-1046-4.

Zhang, B., Wu, P., Zhao, X., Wang, Y., Gao, X., 2013. Changes in vegetation condition in areas with different gradients (1980–2010) on the Loess Plateau, China. Environ. Earth Sci. 68, 2427–2438. https://doi.org/10.1007/s12665-012-1927-1.

Zhao, H.L., Zhao, X.Y., Zhou, R.L., Zhang, T.H., Drake, S., 2005. Desertification processes due to heavy grazing in sandy rangeland, Inner Mongolia. J. Arid Environ. 62, 309–319. https://doi.org/10.1016/j.jaridenv.2004.11.009.

Zhao, G., Mu, X., Wen, Z., Wang, F., Gao, P., 2013. Soil erosion, conservation, and eco-environment changes in the Loess Plateau of China. Land Degrad. Dev. 24, 499–510. https://doi.org/10.1002/ldr.2246.

Zhou, G., Zhang, X., 1995. A natural vegetation NPP model. Acta Phytoecologica Sin. 19, 193–200.

Zhou, Z.C., Gan, Z.T., Shangguan, Z.P., Dong, Z.B., 2010. Effects of grazing on soil physical properties and soil erodibility in semiarid grassland of the Northern Loess Plateau (China). Catena 82, 87–91. https://doi.org/10.1016/j.catena.2010.05.005.

Zhou, D., Zhao, S., Zhu, C., 2012. The Grain for Green Project induced land cover change in the Loess Plateau: a case study with Ansai County, Shanxi Province, China. Ecol. Indic. 23, 88–94. https://doi.org/10.1016/j.ecolind.2012.03.021.

Zhu, H., Fang, Z., Yang, G., Zhao, X., Dong, K., 2010. Biomass formation and selective absorption for K+/Na+ of *Elymus dahuricus* grown in different saline grassland. Acta Agrestia Sin. 18, 383–387.